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Personalization of Adaptive Learning Modules: Differential Impact Analysis Based on Students' Prior Knowledge Profiles and Self-Regulated Learning Levels

Sudi Dul Aji[1], Nurul Ain[2], Akhmad Zaini[3], Hestiningtyas Yuli Pratiwi[4], Kadek Dwi Hendratma Gunawan[5], Salsabila Kholifahtun Nisa'[6], Muhammad Nur Hudha[7*]
[1,2,3,4]Universitas PGRI Kanjuruhan Malang, Indonesia.
[5,6,7*]Universitas Sebelas Maret, Indonesia.
*Corresponding Author. Email: hudha.mn@staff.uns.ac.id

Abstract: This study aims to identify student learner profiles based on a combination of prior knowledge and Self-Regulated Learning (SRL) levels and to analyze the differential impact of an adaptive learning module on knowledge and SRL improvement in each profile. Using a mixed-methods explanatory sequential design, 92 undergraduate physics education students were selected through purposive sampling. K-Means cluster analysis was applied to form learner profiles, followed by a six-week pre–post intervention and qualitative interviews. The results identified three learner profiles (Proficient-Autonomous Learner, Resilient-Developing Learner, and Proficient-Fragile Achiever). The result showed that the adaptive module significantly improved Results showed significant knowledge gains across profiles, while SRL improvements differed significantly. The Proficient–Fragile Achiever group demonstrated the largest SRL gain ($p < .001$; large effect size, $d > 0.80$), associated with more frequent scaffolding support. In conclusion, the effectiveness of adaptive modules is highly dependent on learner profiles, with the most significant benefits in their ability to provide external support for building self-regulation skills. These findings imply that learning technology design should incorporate SRL as a key variable for personalization, and institutions can utilize these platforms as intervention tools for students with weak learning independence.

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Introduction

Higher education is currently undergoing a significant shift toward personalized learning, a transformation driven by advances in digital technology (Ayu et al., 2023). Adaptive learning systems are at the center of this shift, offering pedagogical innovations in which content, feedback, and learning paths are dynamically tailored to the needs of each student (Cochrane et al., 2014). Using algorithms to respond to student performance in real-time, these platforms are designed to maximize learning effectiveness by presenting the right challenges at the right time. Numerous studies have demonstrated that this approach can significantly improve learning outcomes and student engagement compared to static, uniform learning methods (Terapan et al., 2023; Yang et al., 2024).

In recent years, the integration of technologies such as artificial intelligence into digital education systems has led to increased discussion of adaptive learning (Khalil et al., 2024). Previous studies have also shown that AI-enhanced adaptive learning can improve the personalization of learning content, efficiency, feedback, and learning performance (Rakhmetov et al., 2025; Ouyang., 2025; Ng et al 2024). However, the effectiveness of this

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digital technology depends on students' metacognitive readiness and self-regulated learning (SRL), as the use of this technology has the potential to support learning autonomy (Sardi et al., 2025; Xu et al., 2025). Thus, adaptive learning is not only about sophisticated algorithms but also the psychological readiness and independent learning strategies of students, so that the relationship between adaptive systems and SLR has become one of the state-of-the-art issues in higher education research (Ouyang., 2025; Sardi et al., 2025).

Self-Regulated Learning (SRL) encompasses a range of important skills: from setting goals and choosing learning strategies to monitoring understanding and adapting when encountering difficulties (Broadbent, 2017; Meredith & Silvers, 2024; Vatankhah et al., 2013). In adaptive systems, SRL is particularly important because, although the platform provides external guidance, ultimate success still requires students to participate proactively, reflect on feedback, and manage their efforts (Dunn et al., 2014). Therefore, the synergy between learning environment design and SRL competencies is a strong predictor of academic achievement (Rafiola et al., 2020).

Although various studies have demonstrated the effectiveness of adaptive learning in general, understanding of “for whom” adaptive systems work best remains limited. Most previous studies evaluated the impact in general terms, an approach that risks overlooking how students with different profiles respond uniquely to these technological interventions. In particular, there is still little research that groups students based on a critical combination of prior knowledge (cognitive aspect) and Self-Regulated Learning (SRL) level (metacognitive aspect) (Anderson & Thomas, 2014).

Conceptually, the interaction between prior knowledge and Self-Regulated Learning (SRL) in learning is not linear but dynamic because the effectiveness of adaptive technology is highly dependent on the characteristics of students' knowledge and self-regulation in a digital environment (Sharma et al., 2024). Students with high prior knowledge but low self-regulated learning tend to exhibit overconfidence, ignore important support, or fail to engage deeply with adaptive feedback, which can lead to performance stagnation in adaptive systems (Munshi et al., 2022). Conversely, students with low prior knowledge but high self-regulated learning often demonstrate persistence, strategic help-seeking, and effective monitoring, enabling them to utilize adaptive guidance more optimally (Munshi et al., 2022). This contrasting pattern suggests that adaptive systems may reinforce existing student characteristics rather than compensate for them, making the combined profile of cognitive and metacognitive readiness a critical determinant of effectiveness (Sharma et al., 2024).

This limited understanding has the potential to have serious practical implications. Without identifying groups, there is a risk that institutional investment in advanced technology will not provide equitable benefits, especially for students who need support. Therefore, an approach that can capture the characteristics of students more comprehensively is needed. A profile-based (individual-centered) approach provides a relevant framework because it allows for the identification of subgroups of students with similar prior knowledge and self-regulated learning. This enables a more precise analysis of differential effects and provides pedagogical insights that can be applied to targeted instructional design. By revealing hidden learner profiles, this study aims to identify student learning profiles based on a combination of prior knowledge and self-regulated learning levels, as well as analyze the different impacts of adaptive learning modules on knowledge and SRL improvement in each profile.

Vol. 12, No. 1 : March 2026
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pp. 251-258
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Research Method

This study used a mixed-methods design with an explanatory sequential model. The first quantitative stage was conducted to identify statistical patterns of the impact of adaptive modules, which were then explored in depth in the qualitative stage to explain "why" and "how" this impact occurred from the students' perspective. The research subjects were 92 physics education students selected through purposive sampling from the "Learning Media Development" course. Participation was voluntary and based on informed consent.

Data collection was conducted using four main validated instruments: (1) diagnostic tests (pre-test and post-test) to measure conceptual understanding, (2) a Self-Regulated Learning (SRL) questionnaire adapted from the MSLQ, (3) system data logs to record student interactions with the module, and (4) semi-structured interview guidelines. The research process began with initial data collection (pre-test and SRL questionnaire), which were analyzed using K-Means to form learner profiles. Next, all students underwent an intervention using adaptive modules for six weeks, which ended with final data collection (post-test, SRL questionnaire, and interviews).

Quantitative data analysis includes descriptive statistics, Paired Sample T-Test to measure the significance of score increases, and ANCOVA to compare the pure effects of the intervention between clusters while controlling for initial scores. Meanwhile, qualitative data from interview transcripts were analyzed using thematic analysis (Braun & Clarke, 2006) to identify patterns and meanings. The findings from both types of analysis are then integrated to provide a comprehensive answer to the research objectives.

Results and Discussion

1) Identifying Student Learner Profiles

A K-Means cluster analysis was conducted on the initial data consisting of pre-test scores (initial knowledge) and Self-Regulated Learning (SRL) questionnaire scores (initial learning independence) from 92 participants (Figure 1). This analysis successfully identified three significantly different learner profiles, which were then named according to the characteristics of their mean scores. Table 1 presents the distribution of participants and the characteristics of the mean scores for each cluster.

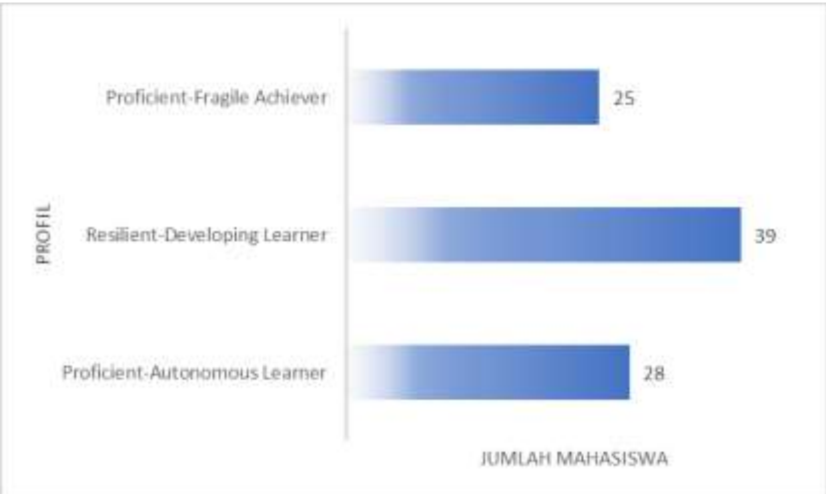

Figure 1. Distribution of Learner Profile Characteristics Based on the Number of Students

Table 1. Characteristics of Learner Profiles Based on K-Means Cluster Analysis of Test Scores

Cluster	Pre-test Average	Post-test Average	Knowledge Improvement
Proficient-Autonomous Learner	85.4	91.2	Significant (p < .001)

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Resilient-Developing Learner	54.2	75.8	Significant ($p < .001$)
Proficient-Fragile Achiever	82.1	90.5	Significant ($p < .001$)

As presented in Table 1, Cluster 1 (Proficient–Autonomous Learner) comprises students with high levels of prior knowledge and substantial learning autonomy. Cluster 2 (Resilient–Developing Learner), representing the largest group, includes students with relatively low prior knowledge but high SRL scores, reflecting strong motivation and effective learning strategies despite limited initial understanding. Cluster 3 (Proficient–Fragile Achiever) constitutes a distinct group characterized by high prior knowledge, comparable to Cluster 1, yet markedly low SRL scores, indicating potential challenges in independently regulating their learning processes.

2) Differential Impact Analysis of Adaptive Learning Modules

The impact of the adaptive module was analyzed by comparing pre-test and post-test scores and initial and final Self-Regulated Learning (SRL) scores. Results from the paired-sample t-test indicated that all clusters experienced statistically significant gains in knowledge ($p < .001$) after using the module for six weeks. However, further analysis using ANCOVA, which compared post-test scores while controlling for pre-test scores, revealed no significant differences in knowledge gain across clusters ($F(2, 88) = 1.76$, $p > .05$). The most notable findings emerged from the analysis of SRL score changes. As presented in Table 2, all groups demonstrated improvements in SRL, though the magnitude of these improvements varied significantly. ANCOVA results confirmed highly significant differences in SRL gains across clusters ($F(2, 88) = 8.42$, $p < .001$).

Table 2. Comparison of Knowledge and SRL Score Improvements Between Clusters

Cluster	Initial SRL Mean	Final SRL Average	SRL Improvement
Proficient-Autonomous Learner	6.1	6.3	Not Significant
Resilient-Developing Learner	5.9	6.4	Significant ($p < .05$)
Proficient-Fragile Achiever	3.5	5.2	Very Significant ($p < .001$)

Specifically, the Proficient–Fragile Achiever group demonstrated the largest and most significant increase in SRL scores, rising from a mean of 3.5 to 5.2. This improvement substantially exceeded that of the other two groups, suggesting that the adaptive module intervention provided the most significant benefit for this learner profile in fostering self-regulated learning.

3) AI Personalization Strategy Analysis and Qualitative Findings

Analysis of the Proficient–Fragile Achiever group, which showed the greatest benefits of Self-Regulated Learning (SRL), was conducted using system log data and interview findings (third research question). Log data analysis showed that the AI algorithm in the module provided different personalization strategies for each cluster. The Proficient–Fragile Achiever group received scaffolding interventions (such as step-by-step guides, deadline reminders, and short formative quizzes) 50% more often than the other two groups. Interview data showed that this higher frequency was generally perceived as structured support rather than distraction. Students reported that reminders and directed prompts helped them manage their time, stay focused, and monitor their understanding. On the other hand, the Proficient–Autonomous Learner group was most often presented with enrichment content and complex case studies, while the Resilient–Developing Learner group most often accessed basic materials and explanatory videos.

The quantitative findings were supported and contextually enriched by qualitative data from interviews, which provided more profound insights into students' perceptions of the personalization features. For instance, a participant from the Fragile Achiever cluster

Vol. 12, No. 1 : March 2026
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pp. 251-258
Email: jklppm@undikma.ac.id

articulated how the system's scaffolding features directly addressed their self-regulation deficits: "*Honestly, I understand the material, but I often procrastinate... The reminder notifications and short quizzes... really helped me stay focused... I felt more organized*." This statement clearly illustrates how the external support provided by the AI functioned as a procedural framework to assist students with low SRL in managing their learning processes. Conversely, a Resilient–Developing Learner cluster participant highlighted the benefits of content adaptation, stating, "*I like it because if there is material I don't understand, I can rewatch the video multiple times without feeling embarrassed. The system also gives easier practice questions first...*" The triangulation of quantitative and qualitative evidence consistently demonstrates that the adaptive module's functions extend beyond content personalization; they also provide differentiated strategic support, which proved most impactful in fostering self-regulated learning among the learner profiles most in need.

Discussion

The findings concerning the three distinct learner profiles Proficient Autonomous, Resilient–Developing, and Fragile Achiever carry important theoretical implications. These results directly challenge the unidimensional perspective that often categorizes students solely based on their prior knowledge (Boogert et al., 2018; D'Elia et al., 2014; Han et al., 2014). The presence of the Fragile Achiever cluster is particularly noteworthy, as it empirically demonstrates a disconnection between content mastery and self-regulation ability (Meredith & Silvers, 2024). This supports the argument that expertise in a given domain does not automatically translate into possessing effective learning strategies (Broadbent, 2017). This profile represents a segment of students who, although appearing cognitively competent, in fact exhibit deficits in metacognitive and motivational functions that are crucial for self-directed learning (Aslamiyah et al., 2019). Conversely, the Resilient–Developing cluster provides concrete evidence for learning models that emphasize the central role of Self-Regulated Learning (SRL) as a compensatory factor for limited prior knowledge and as a key predictor of academic resilience (Dunn et al., 2014).

The main finding of this study is that the most significant improvement in SRL scores occurred in the Fragile Achiever group. This result can be explained within the theoretical framework of cognitive scaffolding. Scaffolding refers to instructional support that enables learners to perform tasks they would not yet be able to accomplish independently (Malik, 2017). In this study, features such as reminders, formative feedback, and structured prompts provided by the adaptive system functioned as external scaffolding specifically targeting self-regulation processes (Frank et al., 2017; Lange et al., 2016; Wass et al., n.d.). This support is assumed to reduce unnecessary cognitive load associated with learning management (Boogert et al., 2018), thereby allowing students to allocate their cognitive resources toward practising the metacognitive strategies modelled by the system. Over time, this external support is hypothesized to be internalized by students, in line with Vygotsky's theoretical principles, ultimately fostering the development of more autonomous and independent SRL capabilities. (Smagorinsky, 2017; Stott, 2016).

The role of the adaptive system in producing these differential effects becomes clearer when analyzing its personalization strategies. The system was shown to adapt at two levels: the content level (delivering remedial or enrichment materials) and the learning-process level, which marks a significant advancement. Process adaptation, particularly through the provision of metacognitive scaffolding for the Fragile Achiever cluster, illustrates the potential of intelligent systems to function as pedagogical agents that foster the development of lifelong learning competencies (Ayu et al., 2018; Jufriadi et al., 2019). This aligns with research suggesting that digital learning environments should not only deliver information but also actively promote cycles of self-regulation (Keller et al., 2023; Kompar, 2018). On the other hand, the absence of significant SRL improvement in the Proficient–Autonomous cluster is most likely attributable to a ceiling effect, whereby their already high initial scores limited the observable room for growth (Boogert et al., 2018; Schrepp et al., 2014). However, this also highlights a challenge for the system: providing sufficiently complex tasks to stimulate further development among expert learners an issue closely related to cognitive load theory and the Expertise Reversal Effect (Boogert et al., 2018; Malik, 2017).

While this study offers significant insights, several limitations remain. The generalization of its findings should be approached with caution, as participants were drawn from a single study program physics education and the measurement of SRL relied on self-report instruments, which may introduce bias. Despite these limitations, the study makes an essential contribution by empirically demonstrating that the effectiveness of adaptive technology is heterogeneous and highly dependent on learners' psychological profiles. The key implication is a call for a paradigm shift in the design and implementation of educational technology: moving beyond content adaptation toward process adaptation that actively supports the development of metacognition and self-regulation

Conclusion

The primary conclusion of this study is that the effectiveness of adaptive learning modules varies significantly, depending on learner profiles influenced by prior knowledge and Self-Regulated Learning (SRL) skills. Specifically, the most significant benefit of this technology lies not in content personalization but in its role as a metacognitive facilitator. The system has been shown to provide structural support (scaffolding) that fosters learner autonomy, particularly for students with high prior knowledge but low SRL. The implications call for a paradigm shift in the design and implementation of educational technology. Theoretically, non-cognitive variables such as SRL should be recognized as core components in adaptive learning models. Practically, instructional designers and educators are encouraged to prioritize process adaptation rather than focusing solely on content adaptation.

Recommendation

Future research should involve larger and more diverse samples to improve the generalizability of findings. Educators are also encouraged to integrate adaptive learning modules based on self-regulated learning to support students with low learning motivation. In addition, future research could explore the long-term impact on the effectiveness of adaptive learning.

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Vol. 12, No. 1 : March 2026
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pp. 251-258
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